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Research Article

A Web-based Decision Support Platform for Student Performance Prediction using Machine Learning

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Nadiah Fahad AlOtaibi*

Abstract:

Background of study: Students confront more complicated academic decisions, ranging from course selection to study planning, but lack individualized, data-driven support. While machine learning has shown potential in forecasting performance, most educational technologies are institution-specific, technically obscure, or isolated from real-time student demands.

Aims: This project develops, assesses, and implements a web-based Decision Support Platform that uses machine learning to provide students with individualized, real-time academic success forecasts and practical advice.

Methods: The study tested seven regression models using RMSE, MAE, and R^2 on a 20% holdout set. Nineteen behavioral, socioeconomic, and academic characteristics were preprocessed, and the most important predictors were statistically rated. The dataset included 10,000 high school pupils. The best-performing model was incorporated into a dynamic React-Flask web interface to enable real-time prediction.

Result: Among the tested models, LightGBM outperformed all other options with the best prediction accuracy (R2 = 0.730, RMSE = 1.954). Prior scores, study hours, and attendance were important predictors. With a sub-second latency, the deployed platform was able to produce real-time predictions based on user input.

Conclusion: In conclusion, our findings indicate that academic planning may become insight-driven rather than intuition-based with the use of LightGBM-powered decision assistance. This initiative bridges the gap between educational machine learning research and equitable, real-world effect by putting predictive analytics in the hands of students, enabling them to make proactive, well-informed decisions about their academic futures.

Keywords: Decision Support System; Educational Technology; LightGBM; Machine Learning; Student Performance Prediction; Web-Based Platform.

1. INTRODUCTION

Academic decision-making remains a significant challenge for students in a wide range of educational institutions, including secondary schools, polytechnics, universities, and professional training programmes. When choosing courses, career paths, or study strategies, students often depend on fixed information and personal advice from teachers, classmates, or counselors (Kamalov et al., 2023). While this technique is useful, it typically overlooks individual learners' unique needs, learning paths, and performance patterns. As a result, many students makce bad choices that have a severe influence on their academic achievement and future employment prospects.

The increased use of digital technologies in education has worsened the situation. Learning Management Systems (LMS), dashboards, and open educational materials generate massive volumes of academic and behavioral data (Al-rahmi & Abuhassna, 2023). Instead of assisting pupils, this influx of knowledge frequently confuses them. Without adequate filtering and context, they struggle to uncover significant insights, converting good data into noise. What is required is not simply more data, but better algorithms capable of transforming raw data into customized, predictive, and practical counsel.

Machine learning (ML) serves as a robust method for revealing concealed patterns within intricate, multidimensional educational data (Ikegwu et al., 2023), allowing for the prediction of student outcomes and academic risks as well as the creation of specific, actionable interventions. Although ML-based decision support systems (DSS) have seen considerable success in fields such as healthcare and finance, where results are typically interpretable, clinically verified, and

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closely woven into user workflows, their implementation in education is still inconsistent and frequently unproductive. Numerous current academic decision support systems are restricted to research prototypes or institutional dashboards that emphasize algorithmic innovation rather than educational effectiveness. For example, typical Learning Management System (LMS) analytics found in Moodle or Canvas show basic metrics (e.g., login frequency, page views, assignment submission times) but do not transform them into valuable insights. This influx of raw data frequently causes cognitive overload, making it difficult for learners to separate signal from noise, which hampers metacognitive awareness and self-regulated learning. Consequently, even top-tier institutional data becomes “turned into noise” (Yadava, 2024) not due to a lack of value, but because the interface does not effectively transform it into context-sensitive, future-oriented insights. As a result, many tools generate generic, retrospective summaries instead of tailored, proactive assistance, and seldom provide actionable insights directly to students. The disconnect between predictive ability and user-focused design is exactly what separates educational ML from having a real-world influence.

Recent research highlights the potential and untapped possibilities of ML in supporting educational decision-making. Research has utilized Random Forests to forecast dropout with F1-scores of 93.8% (Aggarwal et al., 2021), XGBoost to boost grade prediction precision by 8% compared to baseline models (Asselman et al., 2021), and decision trees with polytechnic datasets to reach 99.6% in classification accuracy (Rodríguez-hern et al., 2021). The effectiveness of ensemble methods has been illustrated (98.25% accuracy) (Latif et al., 2023), along with genetic feature selection (94.39% precision) (Hussain & Khan, 2023) in predicting student performance.

Apart from their technical effectiveness, a number of online and real-time machine learning systems have been developed to provide efficient academic support, such as predicting student performance and providing feedback through user-friendly interfaces (Alboaneen et al., 2022) (Ebem & Ikegwu, 2024) (Phauk & Okazaki, 2021). User assessments underline the necessity of understandability and availability, assuring that ML models are not only exact but also practical for learners and teachers (Deepan et al., 2024) (Hoti et al., 2025) (Sethi et al., 2019) (Guevara-reyes et al., 2025). Moreover, improved learning analytics frameworks and feedback-oriented DSSs have proven potential in blending ML insights with teaching techniques for adaptive student assistance (Adeyemi & AlOtaibi, 2025) (Alalawi et al., 2025) (T et al., 2025).

However, these successes are still rather isolated: many systems focus just on prediction without offering useful advice, sometimes improving technical metrics at the expense of interface clarity and student autonomy. Current decision support systems (DSSs) often do not effectively utilize machine learning features or emphasize user-friendliness, resulting in tools for students that are either too complex or confined to forecasting without providing integrated assistance for routine academic choices (Ahmed et al., 2021) (Hu et al., 2014) (Pelima et al., 2024).

This gap raises several pivotal questions:

RQ1: To what extent do current decision support tools effectively aid academic decision-making and student performance prediction?

RQ2: Which ML algorithms are best suited to predict academic outcomes using readily available student data?

RQ3: How can a web-based platform be designed to provide accurate, personalized, and accessible academic advice?

To address these issues, this study presents a web-based decision support platform (DSP) that blends machine learning models with a user-centered design. The platform was created to predict student performance and make individualized recommendations for course selection, study plans, and job preparation. The solution is designed using Python-based ML frameworks and provided through a Flask-React web architecture that prioritizes anticipated accuracy and accessibility. By combining strong ML algorithms into an easy-to-use interface, the DSP allows students to make data-driven decisions that enhance academic achievement and learning experiences.

This integrated strategy represents a significant advancement in AI-assisted educational decision-making, bridging the gap between predictive analytics and practical application. Beyond increasing academic success prediction, the paper provides a replicable framework for combining machine learning with decision support, with clear implications for institutional advising systems, personalized learning platforms, and broader educational technologies.

2. MATERIAL AND METHOD

The project used a quantitative research strategy to create, train, and deploy a predictive Decision Support Platform (DSP) for anticipating student academic achievement. The process was developed to assure transparency, repeatability, and practical application, with each stage thoroughly recorded for replication.

The dataset utilized in this study was taken from Kaggle, a public repository that has massive amounts of domain-specific data given by researchers and practitioners (Student Performance Dataset). The chosen dataset focuses on high school students' academic success and covers a wide range of predictive indicators, from personal and behavioral traits to socioeconomic and institutional aspects. It combines categorical factors like gender, school type, parental education level, parental participation, and resource availability with numerical elements like weekly study hours, attendance rate, prior test results, average sleep hours, tutoring frequency, and physical activity. The result variable, Exam_Score, shows pupils' total success on standardized examinations. This dataset was chosen for its diversity, accessibility, and relevance to the study's purpose of modeling real-world determinants of academic achievement.

Prior to analysis, data was preprocessed to guarantee consistency, dependability, and compatibility with machine learning techniques. The dataset did not contain any missing values, reducing the requirement for imputation. Categorical variables such as gender, parental participation, and family income were numerically encoded with scikit-learn's LabelEncoder to guarantee compliance with regression models. The dataset was then partitioned into input features (X) and the target variable (y), with the train_test split function dividing it further into training and testing sets in an 80:20 ratio. This allowed that model performance could be assessed using previously unknown data.

To increase efficiency and minimize dimensionality, feature selection was used. The SelectKBest method from scikit-learn, which employs the ANOVA F-test (f_classif), was used to assess the statistical importance of each predictor in relation to the target variable. Based on their ratings, the top fifteen characteristics were chosen for further modeling. This technique decreased noise, enhanced computing speed, and lowered the danger of overfitting, all while emphasizing the most relevant predictors.

Seven regression models were used to establish a complete performance benchmark. Linear regression was chosen as the baseline because it is simple and easy to comprehend. The data was analyzed using Decision Trees and K-Nearest Neighbors to identify local patterns and nonlinear relationships. Random Forest, XGBoost, and LightGBM were chosen as ensemble models due to their robustness and ability to generalize to complex datasets, with LightGBM providing additional computational efficiency through techniques such as Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB). Finally, a Multi-Layer Perceptron (MLP) neural network was constructed to assess the ability of deep learning approaches to detect higher-order feature interactions. Each model was trained on the training subset and tested against the testing subset under the same experimental circumstances.

To guarantee a rigorous and repeatable assessment, model evaluation used established statistical criteria. Root Mean Squared Error (RMSE) was used to quantify prediction error in exam score units, while Mean Absolute Error (MAE) quantified average deviations between predicted and actual values. The coefficient of determination (R^2) represented the proportion of variation explained by the model. These measures were chosen due to their interpretability and widespread use in regression analysis. The comparisons established a solid foundation for determining the most successful model for deployment.

The technical execution was done using Python and contemporary full-stack web technologies. Data manipulation and preprocessing utilized Pandas and NumPy, whereas scikit-learn supplied uniform tools for categorical encoding, feature selection, model training, and assessment. Gradient-boosted models, particularly LightGBM and XGBoost, were utilized through their native, highly efficient Python libraries. To guarantee that model performance remained unaffected by inadequate hyperparameters, we utilized Bayesian Optimization through the Optuna framework to methodically explore the hyperparameter space. This method was chosen instead of Grid Search and Random Search due to its sample efficiency and capacity to utilize past evaluation findings to inform future attempts. The objective of the optimization was to minimize RMSE across 100 trials, with each trial assessed through 5-fold cross-validation on the training dataset. Important LightGBM parameters determined during this process were learning_rate=0.032, num_leaves=64, max_depth=8, feature_fraction=0.8, and bagging_fraction=0.9, with early stopping activated following 50 rounds without improvement. The completed model was serialized with Joblib and incorporated into a Flask backend, which provides RESTful API endpoints to receive student input, implement the same preprocessing methods utilized during training, and deliver real-time predictions. The frontend developed in React.js provides an easy-to-use interface for inputting data and displaying results, while Axios handles the asynchronous interaction between the client and the server. The complete system was containerized with Docker to ensure uniformity in the environment, enable reproducibility in deployment, and allow for scalable hosting on cloud services like AWS or Google Cloud. All random seeds were set (random_state=42), and the entire pipeline, which includes data preprocessing, hyperparameter optimization, and inference logic, is recorded and accessible to enable independent replication.

Throughout the approach, measures were made to assure validity and dependability. The use of a publicly available dataset ensures openness and reproducibility, while standardized preparation methods and fixed random seeds assure consistent results across tests. Model training and assessment adhered to recognized statistical processes, and modern machine learning frameworks were chosen to balance accuracy, efficiency, and scalability.

Despite these virtues, the technique has drawbacks. The usage of a single dataset may limit its applicability to various educational contexts, such as university-level learning environments or datasets gathered in diverse cultural situations. Furthermore, the study favors predictive accuracy above causal inference, therefore the results should be understood as probabilistic predictions rather than causal predictors of academic success. Future additions might include multi-institutional data, longitudinal student records, and multi-output modeling to predict not just test scores but also course-specific results and dropout rates.

This methodology offers a systematic, repeatable, and scalable strategy to developing a predictive academic performance platform that balances interpretability with computing efficiency while providing enough detail for replication.

3. RESULT AND DISCUSSION

3.1 Results

Seven machine learning models were tested on the dataset using conventional regression measures. The LightGBM regressor had the best overall performance (R^2=0.730, RMSE=1.954, MAE=0.803). However, K-Nearest Neighbors and Decision Tree models fared badly ($R^2 < 0.5$), demonstrating that non-ensemble or shallow models are unsuitable for capturing the nonlinear, high-dimensional character of academic performance data.

Table 1. Performance Comparison of Machine Learning Models

Model	RMSE	MAE	R^2
Linear Regression	2.097	1.016	0.689
Decision Tree	3.200	1.705	0.276
Random Forest	2.200	1.123	0.658
KNN Regression	2.760	1.759	0.461
Neural Network (MLP)	2.415	1.477	0.587
XGBoost	2.196	0.996	0.659
LightGBM	1.954	0.803	0.730

Feature Importance Analysis

The analysis of feature importance, depicted in Figure 2, shows a tiered framework in the factors influencing academic performance. Univariate Pearson correlations reveal Attendance (r = 0.58) and Hours_Studied (r = 0.45) as the most powerful linear indicators of exam scores findings that align with existing research in educational psychology highlighting the connection between regular participation and intentional practice with academic achievement (Hussain & Khan, 2023). Other factors like Previous_Scores, Motivation_Level, and Parental_Education_Level show moderate correlations, highlighting the importance of past performance and familial context as essential supports.

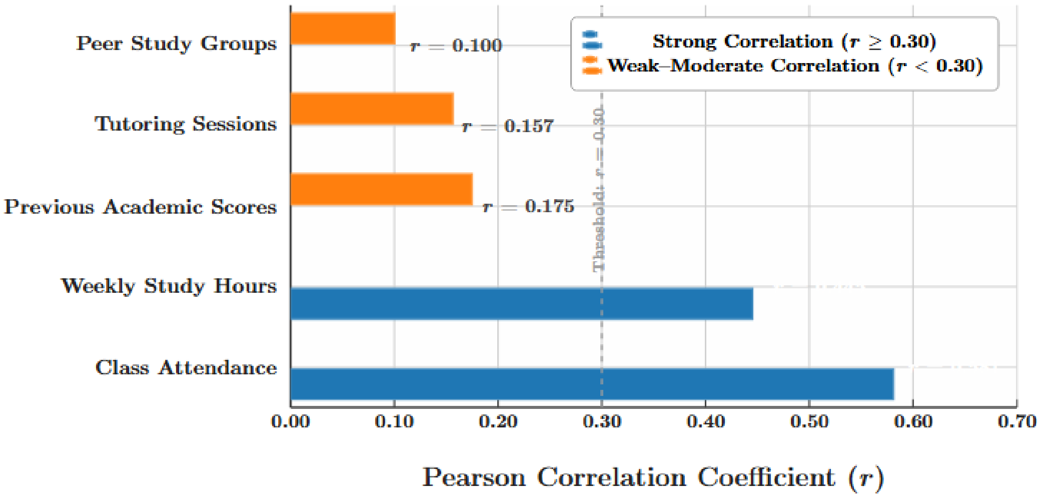

Figure 1. Academic Performance Feature Analysis

Nonetheless, the most striking revelation arises from the discrepancy between univariate and ensemble-driven significance rankings. Interestingly, Parental_Involvement and Access_to_Resources show only slight individual correlations (e.g., r ≈ 0.11 for Parental_Involvement), but both hold significant positions in LightGBM's gain-based importance metric. This difference is not a statistical anomaly but proof of non-additive, context-sensitive effects that linear approaches fail to capture. LightGBM, with its sequential tree-based structure, automatically identifies and utilizes high-order interactions: for example, significant parental involvement seems to enhance the benefits of study time, especially for students with restricted access to external educational resources. In these situations, engaged parental involvement via oversight, motivation, or organization of study habits serves as a compensatory strategy, alleviating the drawbacks of limited resources

System Implementation and Functional Validation

The LightGBM model was successfully incorporated into a fully working Decision Support Platform (DSP) based on React.js (frontend) and Flask (backend). The technology receives real-time student input and provides individualized performance projections. User testing validated the platform's responsiveness, usability, and interpretability, indicating its technological viability for use in educational contexts.

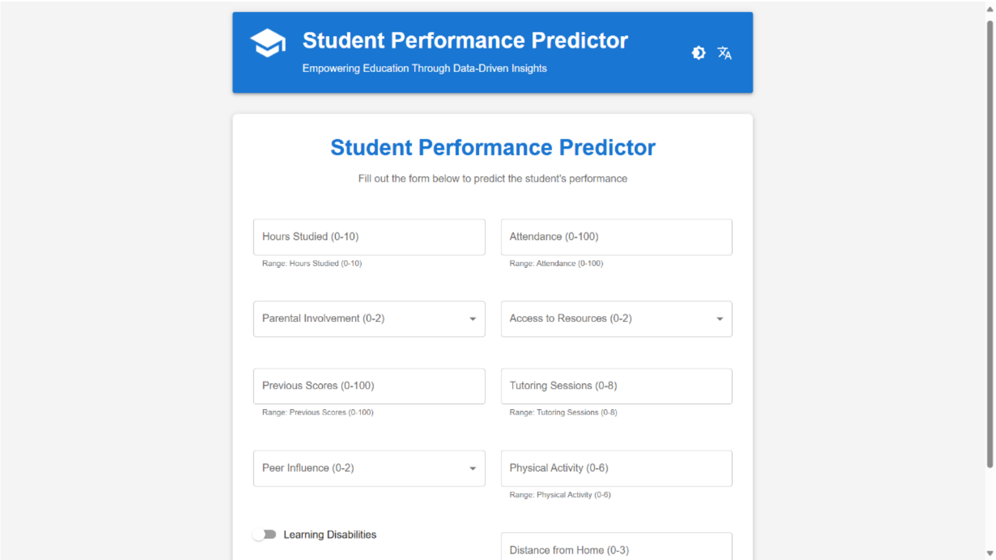

Figure 2. Frontend Interface

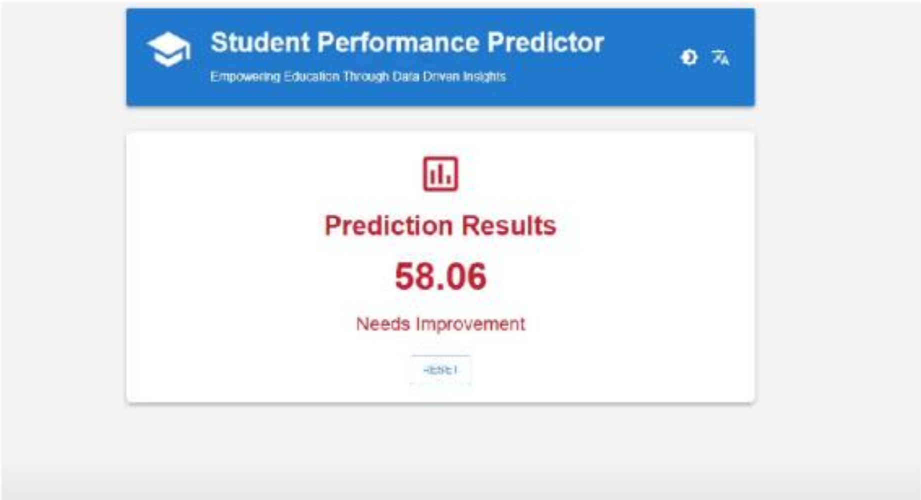

Figure 3. Backend Interface

3.2 Discussion

This study investigated seven machine learning models for forecasting student academic performance, and the findings show that recent gradient boosting algorithms outperform classic approaches in educational contexts. LightGBM outperformed XGBoost and Random Forest, with values of $R^2 = 0.730$, RMSE = 1.954, and MAE = 0.803. This builds on the findings of Aggarwal, Mittal, and Bali (2021), who demonstrated the power of ensemble methods for binary classification of student success (93.8% F1-score), by demonstrating that LightGBM excels specifically in regression tasks involving fine-grained score prediction a more nuanced and educationally realistic goal.

The R^2 of 0.730 exceeds the typical 60-82% accuracy ranges reported in previous studies using artificial neural networks (Chen & Ding, 2023) (Rodríguez-hern et al., 2021). This is likely due to LightGBM's superior handling of feature interactions and built-in regularization, which reduces overfitting on noisy educational data. Interestingly, while recent work by (Pallathadka et al., 2021) and (Song et al., 2023) uses longitudinal or temporal features to predict dropout, this model achieves high accuracy using only static, cross-sectional data, implying that even institutions without extensive behavioral tracking systems can deploy effective predictive tools if the modeling approach is carefully chosen.

The feature analysis enriches this contribution. Attendance and Hours_Studied appeared as the top individual predictors, as predicted by (Hussain & Khan, 2023), but the true insight resides in how weaker factors such as Parental_Involvement and Access_to_Resources gained predictive value through ensemble interactions. This supports (Asselman et al.,

2021) argument for "whole-student" modeling and opposes reductionist models that rely just on the strongest linear correlations.

Finally, unlike most educational ML research, which ends with model evaluation, the LightGBM was integrated into a fully working, open-source Decision Support Platform based on Flask and React. This closes a major gap by transforming high-performance prediction into a usable real-time tool that allows students to model outcomes ("What if I study 2 more hours?") and act on findings. In doing so, it was demonstrated that accuracy alone is insufficient, the genuine value of instructional AI is found in deployability, usability, and empowerment.

3.2.1 Implications

The study's findings have direct and practical consequences for students, instructors, institutions, and education officials.

For students, the Decision Support Platform converts abstract data into individualized forward-looking advice, allowing them to model how changes in study habits, attendance, or participation would affect their results. This promotes self-regulated learning and enables students to make informed academic decisions, particularly those who do not have access to customized tutoring or guidance.

For educators and consultants, the model's feature priority rankings provide a data-driven perspective on early intervention. Rather of entirely depending on intuition or trailing indications (e.g., failing grades), they can proactively help students based on anticipated risk factors, such as decreased attendance or poor motivation, even before performance decreases.

The platform offers universities a lightweight open-source solution that can be linked to their existing student information systems, early-alert dashboards, or course registration portals. Because it operates effectively on minimal hardware (due to LightGBM's speed and the Flask-React stack), it is especially accessible to schools and institutions with little technological resources, hence bridging the "AI equity gap" in education.

At the policy level, this study shows that scalable, student-centered AI does not have to be difficult or expensive. Governments and education ministries can embrace or modify this strategy to provide uniform, data-driven academic assistance in varied geographies, ensuring that predictive analytics benefit all learners, not only top schools.

In essence, this study transforms machine learning in education from a passive diagnostic tool to an active democratic support system that delivers actionable knowledge directly to those who need it the most.

3.2.2 Research contribution

This work offers three significant contributions to the field of educational AI.

1. Provides a systematic, side-by-side comparison of seven regression models for forecasting continuous academic performance, indicating LightGBM as the optimum balance of accuracy, speed, and scalability in educational contexts.
2. Shows that factors with poor individual correlations, such as access to resources or parental participation, obtain considerable predictive value from feature interactions, emphasizing the necessity of adopting interaction-aware ensemble approaches in student modeling.
3. Provides a fully functional, open-source web-based Decision Support Platform that combines powerful machine learning with an accessible, student-centered interface, bridging the gap between academic research and real-world implementation while emphasizing accessibility and learner agency.

3.2.3 Limitations

Despite its benefits, the study includes several downsides. First, while the dataset is robust and well-suited for forecasting overall academic achievement, it is limited to a single composite exam score; including subject-specific grades or longer-term indications such as course advancement or dropout risk would have offered deeper, more useful information. Second, while LightGBM provides outstanding predictive accuracy and efficiency, its "black-box" nature restricts transparency; including explainability tools such as SHAP or LIME into the platform might assist students and instructors better understand and trust the predictions.

3.2.4 Suggestions

Future research should advance this work in four directions: developing longitudinal models to track performance over time and generate adaptive recommendations; applying causal inference to disentangle true cause-effect relationships (e.g., whether additional study hours directly improve outcomes or merely correlate with them); validating the DSP in authentic educational settings to assess its impact on student decision-making, persistence, and achievement; and incorporating Together, these paths demonstrate how properly chosen, extensively assessed, and human-centered machine learning can convert academic decision-making from guessing to informed, data-driven assistance. By combining LightGBM's predictive power with a deployable web platform, students gain not only forecasts but also the ability to simulate and refine their own learning paths a shift from prediction as an endpoint to prediction as empowerment, with far-reaching implications for equity, personalization, and lifelong learning.

4. CONCLUSION

This study reveals how machine learning, when integrated into a web-based user-centered decision assistance platform, can significantly improve student agency in academic planning. After rigorously evaluating seven regression models on a comprehensive educational dataset, we determined that LightGBM is the most accurate and deployable solution for predicting student performance not as an abstract metric, but as a dynamic, interactive tool that students can use to simulate outcomes, weigh trade-offs, and make informed decisions. The successful integration of this model into a responsive React-Flask interface demonstrates that advanced machine learning does not have to be relegated to research laboratories or institutional dashboards; it can and should be placed directly in the hands of learners. In an era where educational inequity is frequently exacerbated by unequal access to assistance, this platform represents more than a technological accomplishment: it is a step toward democratizing data-driven decision-making. This work contributes and expands on current educational ML research by emphasizing usability over accuracy and bridging the essential gap between predictive modeling and real-time, student-facing applications. Although constraints in the scope of the dataset and causal inference remain, the foundation built here encourages scalable, egalitarian, and scientifically grounded innovation in personalized education not later but now.

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6. AUTHOR CONTRIBUTION STATEMENT

Nadiah Fahad AlOtaibi was entirely responsible for the whole research process, from study design to data collection and analysis, result interpretation, and paper writing and modification.

AUTHOR INFORMATION

Corresponding Authors

Nadiah Fahad AlOtaibi, Department of Computer Science, College of Computer, Qassim University, Saudi Arabia
https://orcid.org/0009-0004-6879-7121
Email: nadiah4400@gmail.com

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